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Modeling the effects of climatic and land use changes on phytoplankton and water quality of the largest Turkish freshwater lake: Lake Beyşehir

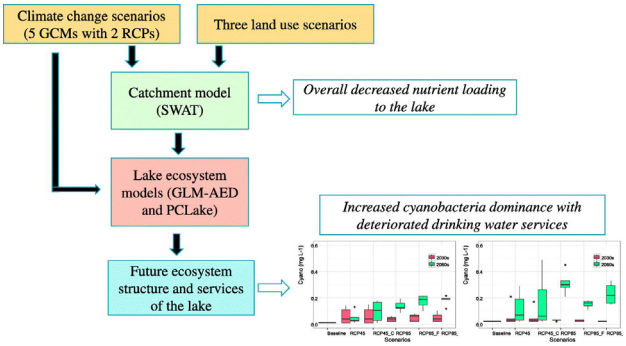
Tuba Bucak [a,*], Dennis Trolle [b,c], Ü. Nihan Tavşanoğlu [a], A. İdil Çakıroğlu [a], Arda Özen [a,d], Erik Jeppesen [b,c], Meryem Beklioğlu [a,e,**]

[a] Limnology Laboratory, Department of Biological Sciences, Middle East Technical University, Çankaya, 06800 Ankara, Turkey
[b] Department of Bioscience, Aarhus University, Vejlsøvej 25, 8600 Silkeborg, Denmark
[c] Sino-Danish Centre for Education and Research (SDC), Beijing, China
[d] Department of Forest Engineering, Çankırı Karatekin University, 18200 Çankırı, Turkey
[e] Kemal Kurdaş Ecological Research and Training Station, Lake Eymir, Middle East Technical University, Ankara, Turkey

HIGHLIGHTS

- We investigated the effect of climate change and land use on ecosystem structure and services.
- We linked process based model (SWAT) outputs to lake ecosystem models.
- Scenarios had major impacts on hydraulic and nutrient loading.
- Increased temperatures and decreased nutrient loading favoured cyanobacteria.
- Cyanobacteria dominance and decreased water level may deteriorate drinking and irrigation services.

GRAPHICAL ABSTRACT


Climate change scenarios (5 GCMs with 2 RCPs)
Three land use scenarios
Catchment model (SWAT)
Overall decreased nutrient loading to the lake
Lake ecosystem models (GLM-AED and PCLake)
Increased cyanobacteria dominance with deteriorated drinking water services
Future ecosystem structure and services of the lake

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SUMMARY

Climate change and intense land use practices are the main threats to ecosystem structure and services of Mediterranean lakes. Therefore, it is essential to predict the future changes and develop mitigation measures to combat such pressures. In this study, Lake Beyşehir, the largest freshwater lake in the Mediterranean basin, was selected to study the impacts of climate change and various land use scenarios on the ecosystem dynamics of Mediterranean freshwater ecosystems and the services that they provide. For this purpose, we linked catchment model outputs to the two different processed-based lake models: PCLake and GLM-AED, and tested the scenarios of five General Circulation Models, two Representation Concentration Pathways and three different land use scenarios, which enable us to consider the various sources of uncertainty. Climate change and land use scenarios generally predicted strong future decreases in hydraulic and nutrient loads from the catchment to the lake. These changes in loads translated into alterations in water level as well as minor changes in chlorophyll *a* (Chl-*a*) concentrations. We also observed an increased abundance of cyanobacteria in both lake models. Total phosphorus, temperature and hydraulic loading were found to be the most important variables determining cyanobacteria biomass. As the future scenarios revealed only minor changes in Chl-*a* due to the significant decrease in nutrient loads, our results highlight that reduced nutrient loading in a warming world may play a crucial role in offsetting the effects of temperature on phytoplankton growth. However, our results also showed increased abundance of cyanobacteria in the future may threaten ecosystem integrity and may limit drinking

* Corresponding author.
** Correspondence to: M. Beklioğlu, Limnology Laboratory, Department of Biological Sciences, Middle East Technical University, Çankaya, 06800 Ankara, Turkey.
E-mail addresses: tuba.bucak@metu.edu.tr (T. Bucak), meryem@metu.edu.tr (M. Beklioğlu).

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water ecosystem services. In addition, extended periods of decreased hydraulic loads from the catchment and increased evaporation may lead to water level reductions and may diminish the ecosystem services of the lake as a water supply for irrigation and drinking water.

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1. Introduction

Climate change is expected to affect lake ecosystem dynamics by altering the quantity and quality of water, possibly resulting in extensive ecological and economic loss (Erol and Randhir, 2012). According to climate projections, the Mediterranean region is one of the most sensitive areas in the world, and a significant reduction in precipitation and an increase in temperature is anticipated for the future (Erol and Randhir, 2012; Christensen et al., 2013). A 3–4 °C increase in air temperatures and a 15–20% decrease in annual precipitation by the end of the century were expected in southern part of Turkey according to projections generated by the Turkish State Meteorological Office (Demir et al., 2013). It is also expected that the demand for freshwater for irrigated crop farming in the Mediterranean region will increase with climate change, which – together with the climate change – may exacerbate the water stress. Reduced water availability may create a significant conflict between sectorial demands (e.g. irrigation and drinking water) and ecosystem needs for maintaining ecosystem structure and functions in freshwaters (Bucak et al., 2017).

The predicted climate change in the Mediterranean is not only expected to decrease water availability (Calbó, 2010), it may also have significant impacts on lake ecosystem structure and function (Beklioglu et al., 2007; Jeppesen et al., 2015). In the semi-arid Mediterranean region, reduced runoff in the catchments may decrease the external nutrient loading to the lakes. However, internal nutrient loading and a reduction of the water volume due to higher evaporation may trigger a nutrient increase (Özen et al., 2010; Coppens et al., 2016; Beklioğlu et al., 2017). Increased temperature and prolonged hydraulic retention time may change the species composition of the phytoplankton and the duration of their blooms, likely resulting in earlier spring blooms (Reynolds et al., 1993; Carvalho et al., 2008; Paerl and Huisman, 2008) and longer duration of autumn blooms. Also, a longer retention time gives an advantage to cyanobacteria over green algae and diatoms (Visser et al., 2015), and prolonged cyanobacteria bloom compromise key ecosystem services such as water supply for drinking or irrigation (Paerl et al., 2011). Additionally, the trophic structure and community composition of the freshwater organisms can be affected by climate warming as evidenced from studies covering large latitudinal and temperature gradients (Jeppesen et al., 2010, 2015).

Management of land and water use is essential to mitigate and adapt to the impacts of climate change. In the Mediterranean region, water availability, demonstrating high seasonal variability, determines the socioeconomic structure (García-Ruiz et al., 2011). An intensive irrigation demand during the least water available season (Morán-Tejeda et al., 2014) poses a risk to freshwater ecosystems and may lead to significant water level reductions, especially in shallow lakes with a high surface area/depth ratio. This, in turn, may result in a degradation of ecosystem structure, function, and services. Moreover, intensive farming can increase nutrient and sediment loads to freshwaters (Foley et al., 2005; Jeppesen et al., 2009, 2015). Enhanced nutrient enrichment is one of the major causes of eutrophication through its direct effects on Chl-*a* concentrations – an indicator of phytoplankton levels – and its indirect effects on oxygen depletion in the water bodies (Jeppesen et al., 2009). All these elements can result in degradation of water quality as well as of a wide range of ecosystem services (Gordon et al., 2010).

Models enable to conduct "virtual experiments" (Meyer et al., 2009), and they are efficient tools for examining ecological questions (Elliott et al., 2000). Over the years, an increasing number of studies have used ecological lake models for management purposes such as combatting eutrophication (Arhonditsis and Brett, 2005a, 2005b), developing mitigation strategies (such as external load reduction and biomanipulation) and predicting the impacts of climate change on lake ecosystems (Trolle et al., 2015; Rolighed et al., 2016). All these extensive research works have triggered the development of ecological lake models advancing from simple regressions to process-based complex dynamic models (Janssen et al., 2015).

Studies focusing on the impacts of climate change are at the core of the lake modeling research due to the necessity of understanding the ecological consequences of climate change and developing adaptation strategies to combat its outcomes. So far, most of the lake modeling studies have been built on single process-based models. However, recently, ensemble modeling, which is commonly employed in climate studies, has been introduced in lake modeling studies as well. For the first time, Trolle et al. (2014) applied ensemble modeling to predict Chl-*a* concentrations by ensembling three different lake ecosystem models for a single lake. This approach not only has a value in understanding the structural uncertainty in model simulations but also provides a possibility to compare different ecological processes schemes (Janssen et al., 2015), allowing development of better prediction powers. In the current study, the future ecological structure of the largest freshwater lake in the Mediterranean basin as well as Turkey, Lake Beyşehir, was simulated by linking catchment model outputs (SWAT) with two different processed based lake models: PCLake and GLM-AED. Our first aim was to perform simulations to understand how climate change and land use practices affect ecosystem structure and function through the lake's capacity to provide services, which are mainly drinking and irrigation water supply. We also aimed to unravel the uncertainties arising from the model selection, climate models and scenarios and to determine the effects of these on the future predictions by using two different lake models, five different climate models and two Representation Concentration Pathways (RCPs).

2. Materials and methods

2.1. Study site

Lake Beyşehir (Fig. 1), the largest freshwater lake in Turkey as well as in the Mediterranean basin, has a surface area of approximately 650 km^2 and mean and max depth of 5–6 and 8–9 m, respectively. The lake is located within the borders of two national parks, Beyşehir and Kızıldağ, the former being the second largest national park in Turkey with a surface area of 86,855 ha, covering 4/5 of Lake Beyşehir (General Directorate of Nature Conservation and National Parks, www.milliparklar.gov.tr). The catchment is situated in a semi-dry Mediterranean climate having an average temperature of 11 °C and an annual total precipitation of 490 mm during 1960–2012. In this period, precipitation values fluctuated between 317 and 716 mm (Beyşehir meteorology station, www.mgm.gov.tr), and the lowest annual average temperature was recorded in 1992 (8.5 °C) the highest in 2010 (13.1 °C).

Lake Beyşehir is located in a tectonic depression area in a northwest-southeast direction in the western Taurus system (Yarar et al., 2009). The lake basin has existed since the Middle Miocene (15.97–11.6 million years ago (Oguzkurt, 2001). Lake Beyşehir is primarily fed by waters from the Sultan and Anamas Mountains and springs from Mesozoic calcareous cracks, precipitation and snow melts. Water from

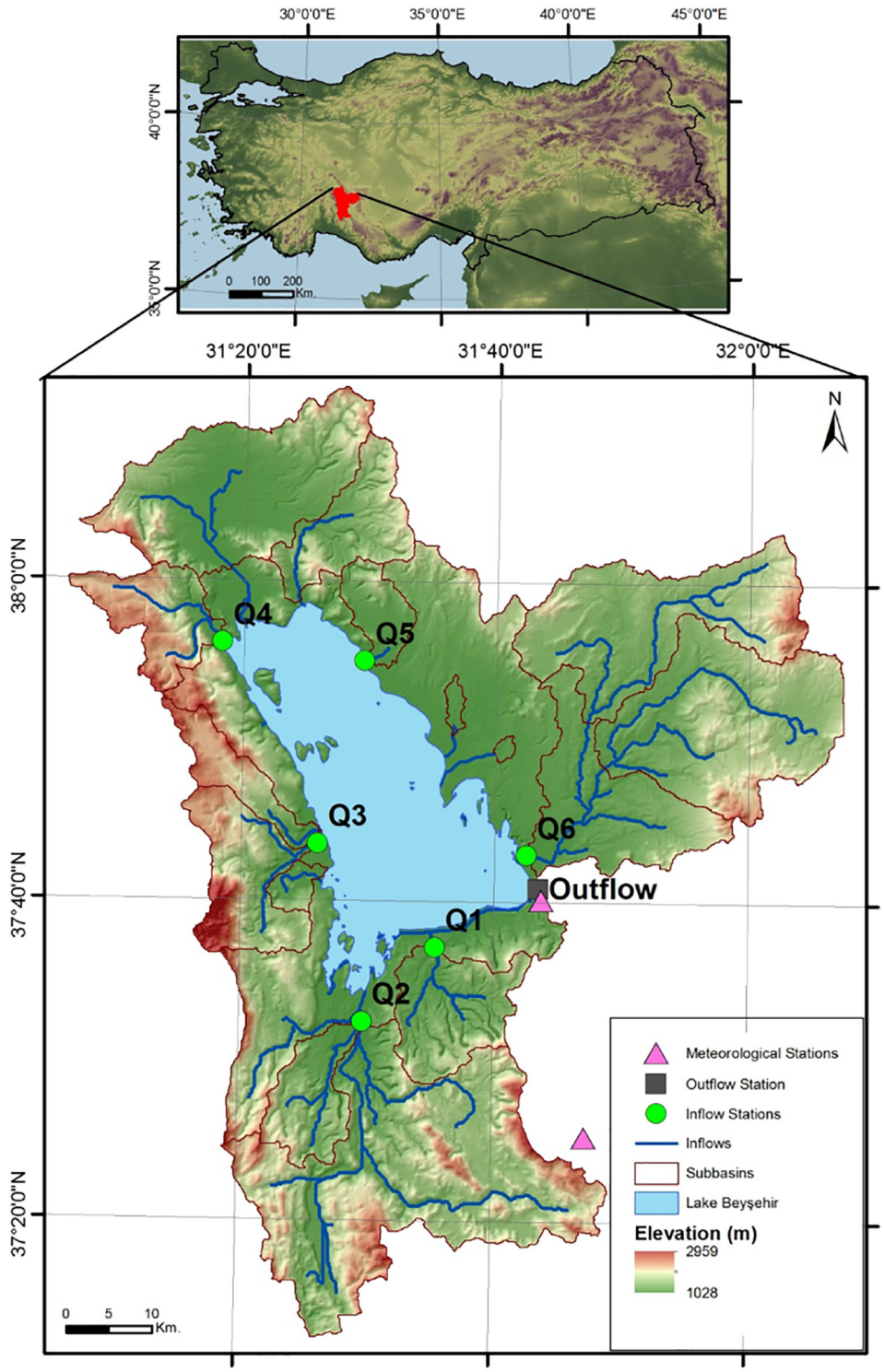

Fig. 1. Location of the study site. Local names of inflows–which were used in calibration– are: Q1: Üstünler, Q2: Soğuksu, Q3: Hizar, Q4: Çeltek, Q5: Tolca-Ozan, Q6: Sarısu).

the lake flows through the Çarşamba stream, to the Suğla Plain, and then to Konya Plain and Salt Lake. Historical and paleolimnological studies have pointed out that the water level of the lake is critical for its ecosystem structure. During low water level periods, expansion of macrophytes has been observed (Beklioğlu et al., 2006). Moreover, low water level periods are characterised by low-light tolerant macrophyte species and dominance of pelagic diatom and cladoceran taxa (Levi et al., 2016). The trophic status of the lake is oligotrophic to mesotrophic, with low phytoplankton biomass and nutrient concentrations. During its history, the lake has experienced several strong disturbances such as sewage effluent discharge, exotic fish introduction, and excessive water withdrawal. The fish species *Sander lucioperca*, which is not native to Turkey, was introduced in 1977 and caused the extinction of the endemic species *Alburnus akili* and drastic changes in fish community structure (Oguzkurt, 2001). *Carassius gibelio*, which is also an exotic species, *Tinca tinca* (from the 1990s onwards), and *Atherina boyeri* (in 2002) have also been introduced to the lake (Innal and Erk'akan, 2006; Yeğen, 2006).

2.2. Modeling

In the current study, a combined approach of catchment and lake models was used for predicting the impacts of climate change and land use on the Lake Beyşehir ecosystem. Hydraulic and nutrient loads were simulated by applying the SWAT catchment model, which has been previously applied in the modeling of hydrological processes (Bucak et al., 2017) in the catchment. In the current study, the model was expanded to calibrate the nutrient exports from the catchment to the lake. The SWAT model setup for the Lake Beyşehir catchment has been explained in detail in Bucak et al. (2017). After running SWAT model, the outputs of SWAT (nitrogen, phosphorus and hydraulic loads) and climate model outputs (temperature and precipitation) were manually fed into the lake models in order to predict the future concentrations of total nitrogen (TN), total phosphorus (TP), Chl-*a* and cyanobacteria and the water level as indicators of the lake's ecosystem structure and capacity to serve as a drinking and irrigation water supply. The two lake models were run independently. For drinking water and recreation water standards, we adopted the World Health Organization's (WHO) limits for cyanobacteria biomass. According to WHO's limits for cyanobacteria biomass, Chl-*a* concentrations should be lower than 10 mg m^{-3}. Low risk is defined as concentrations between >10 mg m^{-3} and <50 mg m^{-3}, while high risk is defined as concentrations >50 mg m^{-3} (Chorus and Bartram, 1999).

2.3. Descriptions of the models

2.3.1. SWAT

The Soil and Water Assessment Tool (SWAT) model was developed by the Agricultural Research Service in the United States, Department of Agriculture (Arnold et al., 1998). SWAT is a physically based continuous model, running on a daily time scale (Neitsch et al., 2011). The model is based on water balance equations, including surface runoff, precipitation (rain and/or snow), evapotranspiration, infiltration, and subsurface flow. Nutrient balance equations are also based on factors like external loading, transportation of nutrients with runoff, fertilizers, plant nutrient uptake amount and soil characteristics (Gassman et al., 2007). The SWAT model considers nutrient cycles and traces the movement of nitrogen and phosphorus in various forms. In the phosphorus (P) cycle, plant P uptake, fertilizer application, mineralisation and decay processes are included, while in the nitrogen (N) cycle plant N uptake, fertilizer application, volatilisation of NH_4, nitrification, denitrification, decay and mineralization processes were included (Neitsch et al., 2011).

2.3.2. General lake model (GLM)

General Lake Model (GLM v2.0.0), a one-dimensional (1D) hydrodynamic model considering variations in the vertical gradient, is coupled to the Aquatic EcoDynamics module library (AED) through the Framework for Aquatic Biogeochemical Modeling (FABM) (Hipsey et al., 2013, 2014). GLM computes the temperature, salinity and density gradients in vertical profiles as a result of inflow, outflow, and meteorological forcings. GLM uses a Lagrangian layer scheme (Imberger and Patterson, 1981) in which the lake is represented by layers that may expand or contract considering density changes driven by surface heating, mixing and flows. Most of the algorithms related to hydrodynamics in GLM are adopted from the widely used hydrodynamic lake model DYRESM (Han et al., 2000; Bruce et al., 2006; Gal et al., 2009; Rinke et al., 2010; Trolle et al., 2011a).

The AED ecological module enables simulation of various chemical processes including inorganic and organic nutrient cycles, oxygen dynamics and biological organisms as functional groups. AED supports oxygen, silica, phosphorus, nitrogen, organic matter, Chl-*a*, phytoplankton, zooplankton and pathogen modules. In the nutrient modules, mineralisation, decomposition, sediment fluxes, uptake by phytoplankton and excretion by organisms are simulated. For the nitrogen module, denitrification and nitrification processes are also included. Phytoplankton biomass is calculated considering nutrient uptake, excretion, mortality, respiration, vertical movement, and grazing by zooplankton. In the zooplankton module, processes of assimilation arising from grazing, respiration, excretion, fecal pellet production, mortality and predation by larger organisms are included (Hipsey et al., 2013).

2.3.3. PCLake

PCLake is a complex dynamic lake model that was developed to simulate nutrient, phytoplankton, macrophyte, and food web dynamics in completely mixed shallow lakes (Janse, 2005). PCLake is a zero dimensional model in which the lake column is represented as completely mixed water body and the top 10 cm of the sediment. It is suitable for shallow lake bodies that are permanently mixed and have no vertical and horizontal variation. Interactions between the water column and the sediment top layer are modelled with specific biogeochemical modules including processes like settling, resuspension, mineralisation, diffusion, and sorption (Janse, 2005). The biological module comprises three groups of phytoplankton, one zooplankton group, one zoobenthos group, planktivorous fish (adults and juveniles), piscivorous fish and submerged macrophytes. Phytoplankton biomass is calculated by taking into account primary production, respiration, mortality, settling, resuspension, grazing and transport processes. All animal groups are modelled as the product of feeding, egestion, respiration, mortality, and predation. Despite having advanced biogeochemical and biological modules, it does not have hydrodynamic and thermodynamic modules (Janse, 2005). However, through the redesigned PCLake model, FABM-PCLake, it is now possible to couple PCLake with one-dimensional and three-dimensional hydrodynamic models (Hu et al., 2016).

2.4. Data requirements of the models

SWAT has previously been calibrated for the study of hydrological processes in the Lake Beyşehir catchment (Bucak et al., 2017). Detailed information and the data requirements for Lake Beyşehir SWAT implementation can be found in Bucak et al. (2017). For the nutrient calibration (N and P) of the SWAT model, and calibration of the lake models, Lake Beyşehir, and its main inflows were surveyed monthly for physicochemical and biological variables within the period of April 2010–March 2012.

To set up the lake models, daily meteorological data and physicochemical variables from the lake's inflows were needed. Both of the lake models require meteorological forcing of precipitation, wind speed and radiation (however, these are not obligatory in PCLake since, as a minimum, water temperature, assuming sinusoidal radiation distribution, must be fed into the model), and GLM-AED additionally requires cloud cover, relative humidity, and air temperature. Meteorological data was derived from the Turkish State Meteorological Service. Monthly nutrient concentrations of the inflows were linearly interpolated (piecewise linear interpolation) to generate the daily data that the models required. Residual flows were calculated from the simple water budget equations considering water level, precipitation, inflow, outflow, and lake area information. Since PCLake does not have a thermodynamic component, the daily simulated temperature was derived through the GLM-AED model and it was used as an input to PCLake. PCLake also requires daily evaporation, which was calculated using the Penman equation (Penman, 1948) including radiation, temperature, wind speed, relative humidity and lake area.

The lake models require initial values for physical (water depth), chemical (N, P, silicate, dissolved oxygen concentrations) and biological variables (phytoplankton biomass, phytoplankton composition, total zooplankton biomass) from the first day of the simulation. For GLM-AED model, also salinity, temperature, and pH were included. Since PCLake enables to define only three different phytoplankton groups, the three most dominant functional phytoplankton groups were selected (cyanobacteria, Chlorophyta and Bacilliarophyta) for use in both models

since these constituted 80% of the total phytoplankton biomass in the lake (Bucak, 2017). Both models allow modeling of one zooplankton group and zooplankton was therefore pooled as one zooplankton group. Details of the sampling and processing of physicochemical and biological variables are given in Bucak (2017).

2.5. Calibration of the models

In the current study, the previously calibrated SWAT model for the hydrological processes in Lake Beyşehir (see Bucak et al., 2017) was expanded to simulate nutrient processes in the catchment. The SWAT model was set up for 2010–2012 since monthly monitoring data on nutrient loadings (P and N) from the lake's inflows was available for only two years. Due to the sparse data, all data points were used for calibration and a separate validation of time series data was not conducted. Nutrient calibration was done using SWAT-CUP software applying the SUFI2 algorithm (Abbaspour, 2013). Calibration was performed for nitrate and soluble reactive phosphorus (SRP) loadings. During calibration, percent bias (PBIAS) was used as an objective function. The most sensitive parameters for nutrient calibration and their fitted values are given in Supplementary Material, Table A.1. To assess model performance based on the calibration results, the performance criteria developed by Moriasi et al. (2007) were used where a per cent bias (PBIAS) $<\pm 25$ is *very good*, $<\pm 40$ *good* and $<\pm 70$ *satisfactory*. It should be noted that these criteria for calibration statistics concern monthly calibration results, while the results of the current study are for daily calibration.

Both lake models contain a high number of parameters. In order to reduce the calibration effort, the most sensitive parameters were determined. The sensitivity index for the parameters was calculated using the equation below (Chen et al., 2002):

$$S_{ij} = \frac{\Delta F_i / \bar{F}_i}{\Delta Parameter_j / Parameter_j}$$

where ΔF_i is the change in variable i corresponding to change in parameter j, $\bar{F}_i$ is the default value of the variable i, $\Delta Parameter_j$ is the change in value of parameter j and $Parameter_j$ is the default value of the parameter j.

Each parameter was adjusted by $\pm 10\%$, except temperature multipliers, which were adjusted by values of ± 0.01. When the sensitivity index was >0.5, it was regarded as a sensitive parameter. The most sensitive parameters were used in the calibration were related with dissolved oxygen, soluble reactive phosphorus, nitrate, ammonium, total Chl-*a*, and cyanobacteria. As no automatic calibration software for the two lake models is presently available, calibration was performed by stepwise, manual trial-and-error adjustment until the best match with a minimum error between observed and simulated variables were obtained. Commonly used metric Root Mean Square Deviation (RMSD), which shows how errors spread out along the best fit, was used as an objective function. The results were also visually inspected to check the seasonal trends. Also, for evaluating the model performance, RMSD, normalized bias, and R^2 were calculated. Results were also compared with the lake modeling statistics from the literature. Calibrated parameters and fitted values are given in Appendix A (Table A.2 and Table A.3). During the calibration, the bottom-up principle was employed; firstly, calibration of water balance, temperature, and dissolved oxygen concentration were obtained, followed by calibration of nutrients and phytoplankton groups (Trolle et al., 2008b).

2.6. Scenarios and storylines

2.6.1. Climate change scenarios

Five different climate models (GFDL-ESM2M, IPSL-CMA-LR, HadGEM, MPI and MIROC), hereafter termed GFDL, IPSL, HadGEM, MPI, MIROC, were used for generating precipitation and temperature for two representative concentration pathways (RCPs): RCP 4.5 and RCP 8.5. The former, RCP 4.5, assumes that greenhouse gas (GHG) emission will peak around 2040, followed by a decline, while the latter, RCP 8.5, assumes that emission will increase throughout the 21st century. GFDL, IPSL, and MIROC climate model outputs were downscaled by Deltares (Ferreira et al., 2016). Downscaled HadGEM and MPI model outputs were compiled from Turkish State Meteorological Office. The period 2006–2015 was used as the reference period, and monthly linear bias correction was derived from the difference between observed climate data and scenario outputs within the reference period. Factors derived from linear correction were applied to projected temperature and precipitation data series using the delta change approach. Two distinct periods, including 2025–2034 and 2055–2064, were chosen for future scenario runs representing the 2030s and 2060s, respectively. For the 2030s, the predicted climate scenarios indicated a $+22$ to -17% change in precipitation, whereas for the 2060s, a precipitation change between a 9% increase and a -30% decrease was foreseen (Table A.4). Temperature outputs indicated a 0.0–1.7 °C increase for the 2030s and a 0.6–4.2 °C increase for the 2060s (Table A.5).

2.6.2. Land use scenarios

Three different storylines (Techno World, Consensus World, and Fragmented World) were developed within the scope of the EU-FP7 funded MARS project on future land use scenarios on possible future economic, environmental, political and climatic changes (O'Neill et al., 2014; Ferreira et al., 2016).

In the Techno World (economic focus) scenario, economic growth is the main focus. Higher economic growth will trigger an increase in the energy demand and resources, resulting in agricultural expansion. In southern Europe, water consumption is expected to increase due to increased agriculture and tourism. In this scenario, 20% of the forest areas and 10% of the grassland are turned into cropland, and the amount of fertilizers used and extent of water abstraction increased by 10%. This storyline was constructed on a combination of shared socioeconomic pathway (SSP-5), (see O'Neill et al., 2014 for SSPs) and climate change scenario RCP 8.5. Hence, in future simulations, the Techno World land use scenario and the RCP 8.5 climate scenario were used together.

In the Consensus World (green focus) scenario, economic growth is as it is today. More effort will be directed at promoting sustainable use of sources. Water consumption will decrease due to the expansion of drought-resistant crops and increased irrigation efficiency. In consequence of increased temperature, 5% of forest areas will be turned into shrubland. In addition, the amount of fertilizers used and extent of water abstraction will decrease by 20% and 10%, respectively. This storyline was based on a combination of SSP-2 (O'Neill et al., 2014) and climate scenario RCP 4.5. Hence, the Consensus World land use scenario and the RCP 4.5 climate scenario were used together.

In the Fragmented World (survival of the fittest) scenario, Southern Europe is anticipated to suffer from economic crisis due to a climate change-induced decrease in agricultural productivity. In this scenario, 30% of forest and 30% of cropland will be turned into shrubland following increased temperatures and decreased agricultural productivity. Fertilizer application and water abstraction will rise by 30%. This storyline was based on a combination of SSP-3 (O'Neill et al., 2014) and climate scenario RCP 8.5. The Fragmented World land scenario and the RCP 8.5 climate scenarios were used together.

2.7. Statistical analysis

To be able to determine if any hierarchical or complex relationships controlling cyanobacteria biomass exist, we also applied Conditional Inference Trees (CIT) analysis with variables of temperature, flow, nutrient loading and in-lake nutrient concentrations. Corrplot (Wei and Viliam, 2016) and Party packages (Hothorn et al., 2006) were used in R version 3.2.5 (R Development Core Team, 2012) for correlation and CIT analysis, respectively.

Table 1
Calibration statistics of SWAT outputs for SRP and nitrate loadings. Q1, Q2, Q3, Q4, Q5 and Q6 are the coding for the inflows. Location of the inflows are given in Fig. 1.

	SRP		Nitrate	
Inflows	PBIAS	R^2	PBIAS	R^2
Q1	5.4	0.30	23.8	0.09
Q2	0.5	0.01	−7.13	0.45
Q3	0.5	0.01	28.8	0.06
Q4	−3.0	0.19	−7.5	0.49
Q5	9.4	0.25	38.3	0.41
Q6	15.1	0.32	−19.2	0.47

3. Results

3.1. Performance of the models

3.1.1. SWAT

Since SWAT calibration for the hydrological compartment has already been performed (Bucak et al., 2017), only the results of calibration for nutrients are given in Table 1. The nutrient calibration results mostly demonstrated a low bias as for nitrate with a PBIAS below <±40 (Table 1). The results showed that simulated and observed nitrate concentrations were in good accordance with low bias; however, R^2 values were low. As for phosphorus calibration, all inflow model calibrations had a low bias with PBIAS <±25. Despite this, R^2 values were mostly low due to the low SRP concentrations of the inflows, sometimes they were even under the detection limit, resulting in lower calibration statistics.

3.1.2. Lake models: PCLake and GLM-AED

The GLM-AED model simulation results for water temperature and the oxygen profile matched well with the observations (Fig. 2, Fig. 3 and Table 2). The output of both lake models for Chl-*a* and SRP corresponded well with the observed values considering the timing of the seasonal variations (Fig. 4). However, the goodness of fit was low owing to the low concentrations (lower than 10 μg L^{-1} for both, sometimes SRP levels were even lower than the detection limits) and due to the absence of strong seasonality (Fig. 4). Regarding the concentrations of NH_4-N and NO_3-N, the simulated results from GLM-AED matched better with those observed, while the PCLake model overestimated the nitrogen compounds. GLM-AED modelled cyanobacteria concentrations reasonably well and captured the autumn peaks in the second year of the calibration but did not fully display the first year's autumn peak. PCLake was able to capture the observed patterns for cyanobacteria, underestimating the autumn peaks, however (Fig. 4).

3.2. Changes in hydraulic and nutrient loads to the lake

There were pronounced variations in the SWAT predictions for total flow (total inflows from the catchment to the lake) and nutrient loadings, which were simulated using five different GCMs. Minimum and maximum ranges and averages for the relative changes in the total flow derived from the five GCMs are shown in Table 3. For the 2030s, the relative changes in the flows are predicted to range from +18% to −49% in the RCP 4.5 scenarios without land use change, while for the 2060s flow rates predictions ranged from +21% to −50%. In the RCP 8.5 scenarios without land use change, the relative changes in flow varied between +1% and −23% for the 2030s and from −35% to −59% for the 2060s. Land use had a minor impact on total runoff (Table 3) but significant effects on the nutrient loading from the catchment (Table 4 and Table 5). For the 2030s, in most of the scenarios, the load of nitrate from the catchment decreased, excepting the Techno World land use scenario with RCP 8.5 climate change scenarios which increased nitrate loads were observed for some of the climate models (Table 4). For the 2060s, all scenarios exhibited decreased nitrate loadings (Table 4). Variations in SRP loads were also significant in the different climate change scenarios. Although average SRP loads declined in most scenarios, in the Techno World scenario with RCP 8.5 scenarios for all GCMs, an increase in SRP loads occurred for the 2030s (Table 5). Changes in flow, nitrate and SRP loadings relative to precipitation and temperature are displayed in Fig. 5, all generally decreasing with increasing temperature and declining precipitation.

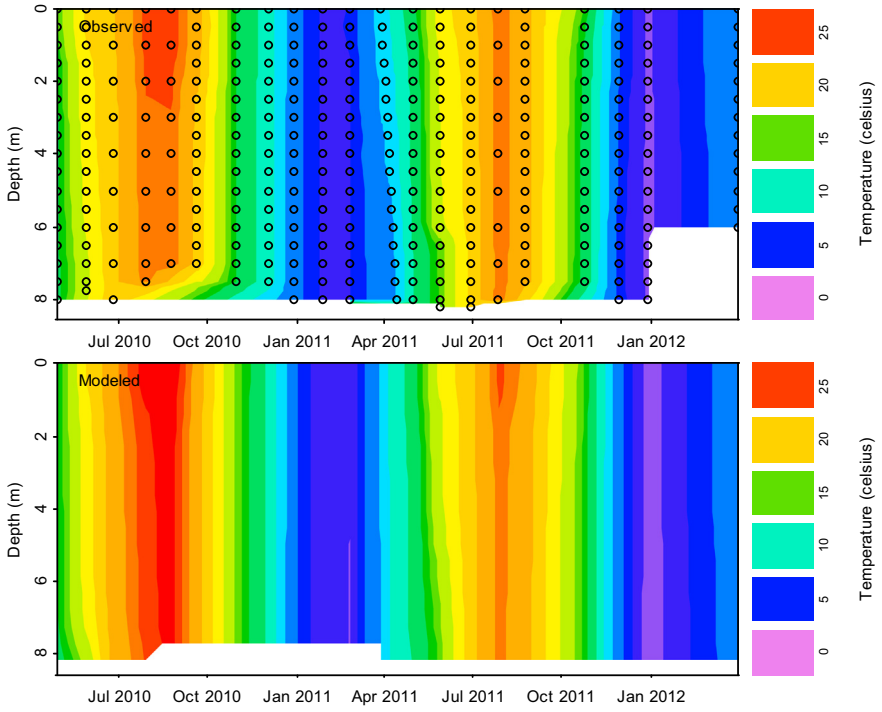

Fig. 2. Comparison of observed and modelled (GLM-AED) water temperatures for the whole water column during the period April 2010–March 2012. Empty circles in the observed plot indicate the corresponding depths of the observed data.

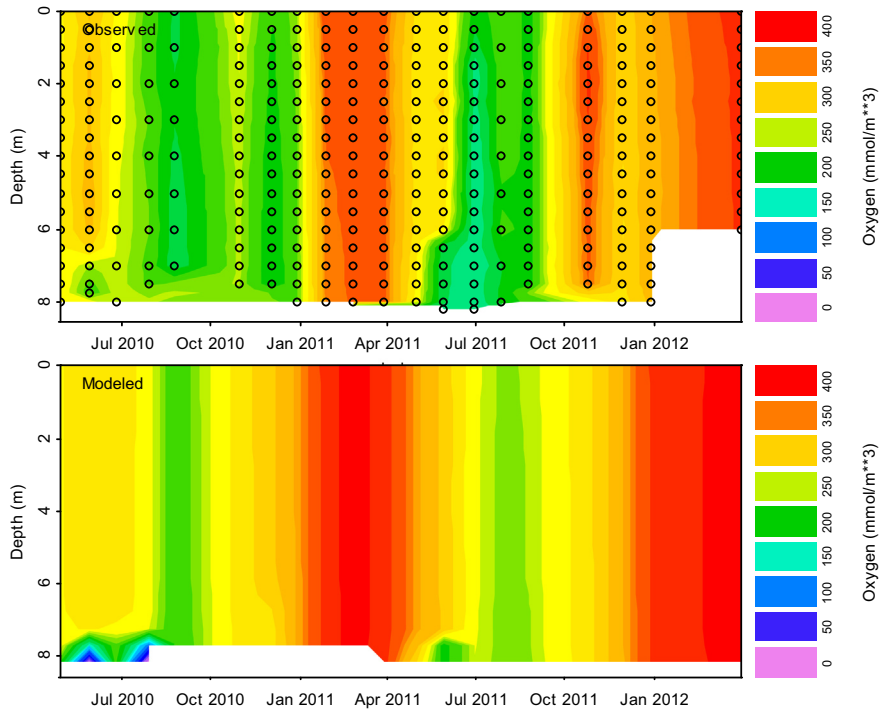

Fig. 3. Comparison of observed and modelled (GLM-AED) dissolved oxygen concentration profiles for the whole water column during the period April 2010–March 2012. Empty circles in the observed plot indicate the corresponding depths of the observed data.

3.3. Changes in lake ecosystem structure and services

The simulated future water levels were mostly lower than the baseline average water level (Fig. 6, Table A.6). Only six and four scenarios for the 2030s and 2060s, respectively, were higher than the baseline water levels (Table A.6). The highest water levels appeared in the Consensus World scenario with RCP 4.5 and the lowest in the Fragmented World scenario with RCP 8.5. The baseline average water level was 8.3 m, while the future water level ranges were 7.77–9.48 m for the 2030s and 7.24–8.78 for the 2060s.

The predictions of the models for TP and TN are presented in Fig. 7. In the GLM-AED model, changes in TP showed less variation than in the PCLake model (Appendix A, Table A.7). The GLM-AED outputs showed minor changes in future TP concentrations compared with baseline TP concentrations in most scenarios.

The PCLake model results demonstrated stronger variation among the different climate models, with a major increase in TP (0.7–1.4 fold, Appendix A, Table A.7) in the RCP 8.5 climate scenarios for all land use combinations in the 2060s (Fig. 7, Appendix A, Table A.7). The GLM-AED model results showed smaller changes in TN concentrations for both the 2030s and 2060s (Fig. 7). However, the PCLake model results exhibited considerable variation in the future scenarios. The highest increase in TN appeared in RCP 8.5 with no land use change and in RCP 8.5 for the 2060s Techno World scenarios where a 1.3–1.4 fold increase in TN occurred compared with the baseline period (Appendix A, Table A.7); the changes for the 2030s were relatively minor.

Lake model predictions for Chl-*a* concentrations and the cyanobacteria biovolume are given in Fig. 8. The GLM-AED model predicted a slight change in Chl-*a* concentrations for both the 2030s and the 2060s compared with the baseline, and the average of the highest Chl-*a* concentrations was around 4 μg L^{-1} in the future scenarios (Appendix A, Table A.8). For most scenarios, the PCLake model generally predicted an increase (0.5–0.9 fold, Appendix A, Table A.7) in Chl-*a* concentrations, which was only prominent for the 2060s, however (Fig. 8, Appendix A, Table A.8). In the worst-case scenario, the average Chl-*a* concentration was around 7.3 μg L^{-1}, which was more than double of the baseline Chl-*a* concentrations (Appendix A, Table A.8).

The predictions of both models for cyanobacteria biomass revealed a major increase in all scenarios, most remarkably for the 2060s (Fig. 8). For both models there was marked variation in cyanobacteria biomass in the RCP 4.5 scenarios (see boxplots in Fig. 8), whereas the variation of the outputs of the RCP 8.5 scenarios was more pronounced, showing a major increase, up to 15-and 17-fold, in cyanobacteria biomass in the PCLake and GLM-AED models, respectively (Appendix A, Table A.7). Moreover, even though all predictions indicated an increase, most results were still under the threshold limits of the World Health Organization (WHO) (Table 6) for drinking water. In the observation period, none of the days exceeded the WHO thresholds. For the 2030s, scenario predictions were still under the low-risk threshold. For the 2060s, 10 scenarios (out of 25) exceeded the WHO limits, and the number of days exceeding the limits are indicated for each scenario in Table 6. For the two-year simulation time, the largest number of days (80) exceeding the WHO low-risk threshold emerged in the HadGEM 8.5 scenario with no land use change.

In the GLM-AED model CIT analysis of cyanobacteria biomass showed that increased temperatures and decreased flow rates favoured cyanobacteria biomass (Fig. 9). However, in the PCLake model, the in-lake TP concentration was the major factor affecting cyanobacteria biomass, followed by temperature and SRP loading to the lake.

Table 2
Calibration statistics for temperature, oxygen, Chl-*a*, SRP, NH_4, and NO_3 for the GLM-AED and PCLake models. R^2: Coefficient of determination, RMSD: Root mean square deviation.

	R^2		Normalized bias		RMSD	
	GLM	PCLake	GLM	PCLake	GLM	PCLake
Temperature	0.99	–	0.025	–	–	0.87
Oxygen	0.68	–	0.45	–	–	1.38
SRP	0.17	0.14	0.34	0.41	2.01	2.4
NH_4	0.14	0.31	0.53	4.17	2.91	11.98
NO_3	0.13	0.03	0.86	8.39	16.39	83.71
Chl-*a*	0.02	0.31	−0.09	0.02	2.66	1.74
Cyanobacteria	0.07	0.22	0.67	1.493	0.012	0.017

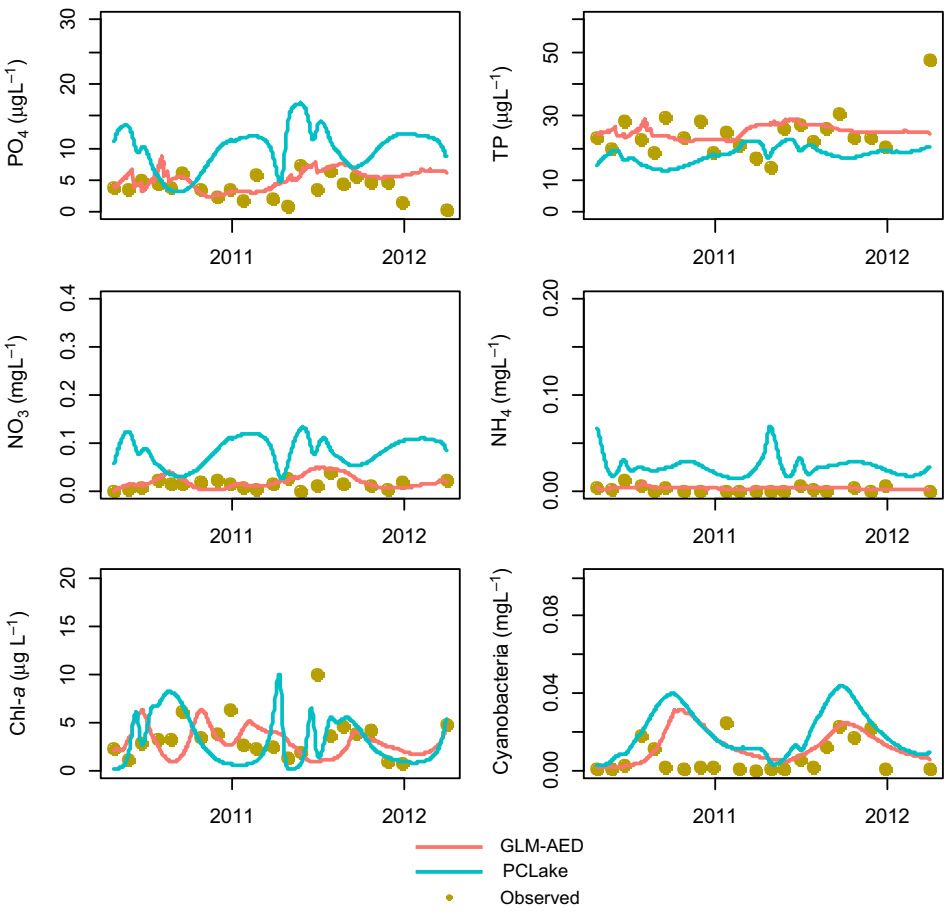

Fig. 4. Calibration results of the lake models together with the observed values for a) PO_4 (SRP), b) TP, c) NO_3-N, d) NH_4-N, e) Chl-*a*, f) cyanobacteria biomass.

4. Discussion

To predict the future nutrient and phytoplankton dynamics of Lake Beyşehir under the impacts of climate and land-use changes, the outputs of the catchment model, SWAT, was linked to two distinct lake models (GLM-AED and PCLake). Our key findings were (i) a strong decrease in total inflows in most scenarios, excluding RCP 4.5 in the 2030s, (ii) nutrient loading was mostly associated with hydraulic loading and the most pronounced decrease in flow led to the most noticeable decreases in nutrient loads, (iii) land use had a minor impact on runoff but a major impact on nutrient loadings, (iv) PCLake and GLM-AED differed slightly regarding simulations of Chl-*a* concentrations. In most scenarios PCLake predicted a future increase in Chl-*a* concentrations, whereas GLM-AED predicted only a minor change in Chl-*a* concentrations (ranging from a minor decrease to a minor increase), (v) both lake models predicted an increase in the contribution of cyanobacteria to phytoplankton biomass, vi) while temperature and flow rate were important drivers of the cyanobacteria biomass in the GLM-AED model, in-lake TP, SRP loading, and temperature were the most significant drivers in the PCLake model, vii) none of the scenarios in either lake model exceeded the low- or high-risk WHO threshold for cyanobacteria concentrations in the 2030s, whereas almost half of the scenarios in the PCLake model exceeded the low-risk threshold in the 2060s, indicating that the lake may periodically not serve as a safe drinking water supply in the 2060s.

The calibration statistics for the SWAT model was acceptable in terms of PBIAS; however, R^2 values were predominantly low. This can be attributed to the low resolution of forcing layers (land use, soil map), which may affect the nutrient transport through the catchment. In addition, ungauged sewage effluent from the nearby towns, not included the model setup, may have contributed to the low calibration statistics. Some of the parameters in the SWAT model can only be

Table 3
Average per cent changes in total flow generated from SWAT using five different GCMs with two RCPs and three land use scenarios. Maximum and minimum relative changes for five different climate change scenarios were computed for the 2030s and 2060s. Current: No land use change. Relative changes were rounded to the nearest integer.

		2030			2060		
Climate	LU	Max	Min	Average	Max	Min	Average
RCP 4.5	Current	18	−49	−18	21	−50	−38
RCP 8.5	Current	1	−23	−9	−35	−59	−46
RCP 4.5	Consensus	22	−46	−15	25	−49	−23
RCP 8.5	Techno	6	−21	−5	−41	−60	−46
RCP 8.5	Fragmented	6	−19	−4	−30	−56	−42

Table 4
Average per cent changes for nitrate loading generated from SWAT using five different climate models with two RCPs and three land use scenarios. Maximum and minimum relative changes for five different climate change scenarios were computed for the 2030s and 2060s. Current: No land use change. Relative changes were rounded to the nearest integer.

		2030			2060		
Climate	Land use	Max	Min	Average	Max	Min	Average
RCP 4.5	Current	−12	−43	−27	−25	−38	−34
RCP 8.5	Current	−11	−42	−29	−28	−48	−39
RCP 4.5	Consensus	−27	−54	−39	−32	−54	−44
RCP 8.5	Techno	18	−31	−3	−19	−46	−34
RCP 8.5	Fragmented	−11	−42	−30	−44	−61	−53

Table 5
Average per cent changes for SRP loading generated from SWAT using five different climate models with two RCPs and three land use scenarios. Maximum and minimum relative changes for five different climate change scenarios were computed for the 2030s and 2060s. Current: No land use change. Relative changes were rounded to the nearest integer.

		2030			2060		
Climate	Land use	Max	Min	Average	Max	Min	Average
RCP 4.5	Current	−8	−83	−38	−28	−70	−46
RCP 8.5	Current	−11	−38	−28	−31	−78	−55
RCP 4.5	Consensus	3.5	−79	−30	−27	−74	−45
RCP 8.5	Techno	51	4.9	22	25	−76	−31
RCP 8.5	Fragmented	8	−21	−9	−8	−81	−47

defined at the catchment scale, and most of the nutrient parameters fitted were catchment-scale parameters (Table A.1). This simplistic approach has some drawbacks as it does not take into account small-scale spatial differences.

We found a decrease in hydraulic loads from the baseline in most of the scenarios, most pronouncedly for the 2060s. Our results concurred with other findings from the Mediterranean region, which also predicted significant decreases in flow in response to climate change (Serpa et al., 2015; Coppens, 2016; Pekel et al., 2016; Shrestha et al., 2017). In Bucak et al. (2017), similar results were obtained using only two GCMs (HadGEM and MPI, also included in this study), the decreases in water availability being more pronounced (15–52%) at the end of the century. In this study, a similar trend emerged in the analysis conducted using an additional three GCMs also, highlighting the potential risk of future water scarcity in Mediterranean catchments. Moreover, we found high uncertainty associated with climate models. This was also the case in Bucak et al. (2017) study where high variability of future predictions of total flows and water levels occurred. Similar to our findings, Shrestha et al. (2017) revealed large variations in flow rates with the simulations of six different GCMs. GCM-related uncertainty has been found in many studies (Wilby and Harris, 2006; Maurer, 2007; Eisner et al., 2012), all highlighting the importance of using ensemble models to obtain more robust future projections.

Nutrient loadings generally followed the same pattern as flows, and higher nutrient reductions were found in the scenarios predicting the lowest total flow. Our results are in line with those of other studies showing interdependence between nitrogen and phosphorus loadings with flow magnitude (Shrestha et al., 2017). However, in our study, the relationship between SRP load and flow was strong, while the relationship between NO_3 and flow was weak. We attribute this to the complex nature of the nitrogen cycle compared with the P cycle in the model. In SWAT, denitrification, nitrification, and nitrogen fixation cycles are included in the model structure, and water availability, soil organic matter and temperature are the mediators of the cycle processes (Neitsch et al., 2011). Nitrogen fixation may also be the mechanism behind the nonlinear relationship between nitrate loading and flow since one of the dominant crop types in the catchment was chickpeas

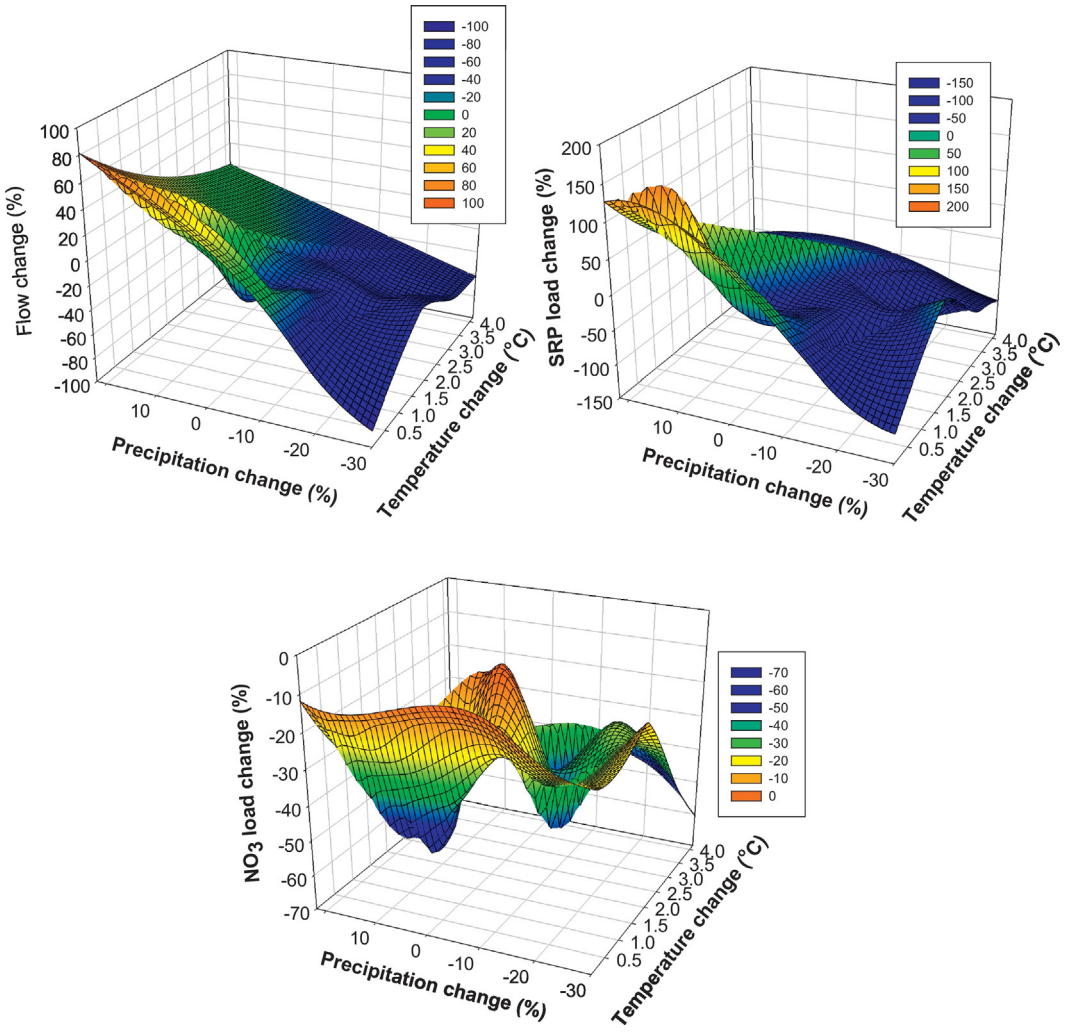

Fig. 5. Per cent changes in average a) total inflow rate, b) SRP load and c) NO_3 load relative to changes in precipitation and temperature.

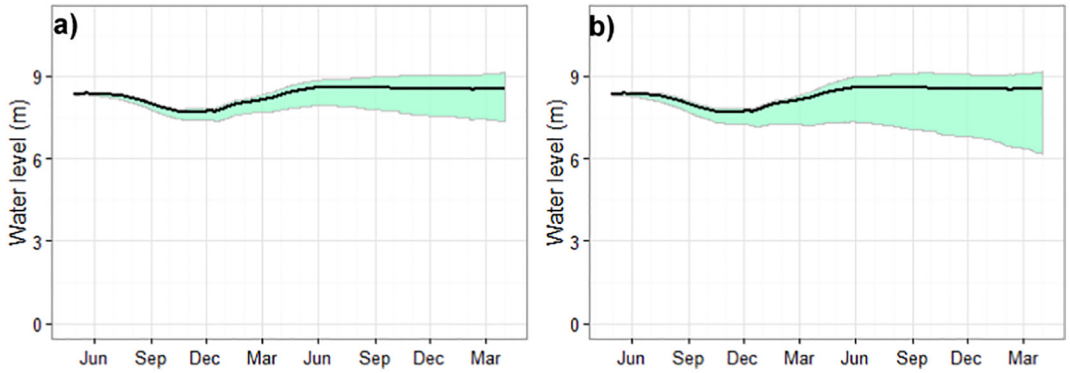

Fig. 6. Future water levels for all climate change and land use scenarios for a) the 2030s, b) the 2060s. Black lines indicate the baseline water level, light green areas indicate the band of all scenario results.

belonging to the legume family. Chickpeas have rhizobia within their root nodules, which enables nitrogen fixation and increases N loading (Carranca et al., 1999).

We found minor impacts of land use on total inflow but major impacts on nutrient loadings. The same pattern has been revealed in several other studies using the SWAT model (Molina-Navarro et al., 2014; Morán-Tejeda et al., 2014; El-Khoury et al., 2015; Shrestha et al., 2017). In mixed land use and climate scenarios, also other factors such as fertilizer and change in land cover seem critical for NO_3 and SRP loadings. For instance, in the Techno World land use scenario, SRP loads increased in the 2030s despite decreased flow rates. Although NO_3 loadings also declined in the Techno World scenario, they were higher than the RCP 8.5 scenarios without no land use change. This can be attributed to an increased extent of agricultural area and enhanced fertilizer application in the Techno World scenario, and a similar pattern has been found in other studies as well (Panagopoulos et al., 2011; Cerro et al., 2014; Molina-Navarro et al., 2014). Changing the land cover from forest to agricultural land decreases the nutrient holding capacity of the system and potentially enhances nutrient leaching and soil erosion (Wischmeier and Smith, 1978). Increased soil erosion is known to be one of the major sources of particulate P from the catchments (Panagopoulos et al., 2011). In addition, increased fertilizer application likely contributed to the higher nitrogen and phosphorus loads in the Techno World scenario. In contrast, nitrate export decreased in the Consensus World scenario with reduced use of fertilizer. All these results concur with the findings from various studies (Jeppesen et al., 2009; Nielsen et al., 2012) showing that expansion of agricultural lands may potentially increase the nutrient loadings from the catchment and threaten the quality of freshwaters; lakes mirror their catchment and catchment processes have a direct influence on lake dynamics.

The calibration statistics of both lake models generally exhibited low R^2 values, which may indicate a lower fit between the observed and simulated variables. However, it should be noted that statistical good fit is not always the main criterion (Grimm, 1994), and that visual fit is also vital (Elliott and May, 2008), depending on the magnitude and range of the data (Elliott et al., 2000). Moreover, low calibration fits

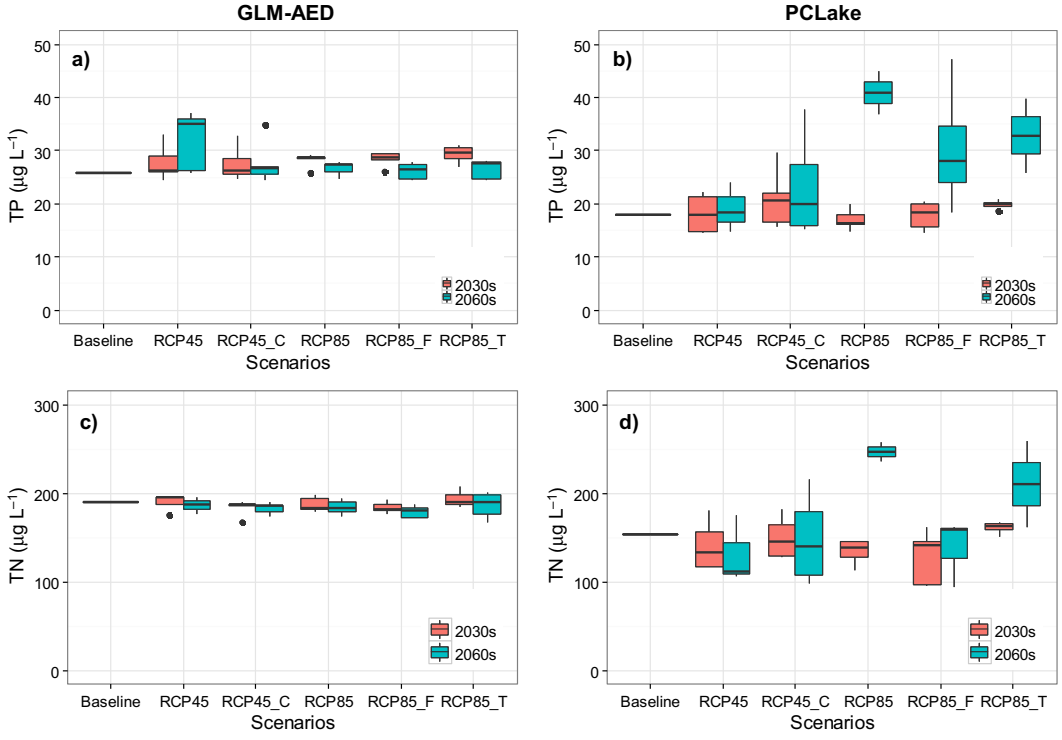

Fig. 7. Lake model predictions for a-b) TP and c-d) TN. Left panels are the results of the GLM-AED model and right panels the results of the PCLake model. RCP 4.5 and RCP 8.5: All GCMs without land use change for the RCP 4.5 and RCP 8.5 scenarios, respectively. RCP45_C: RCP 4.5 with the Consensus World Scenario; RCP 85_F: RCP 8.5 with the Fragmented World Scenario; RCP85_T: RCP 8.5 with the Techno World Scenario. Each boxplot was generated using averages of each GCM result.

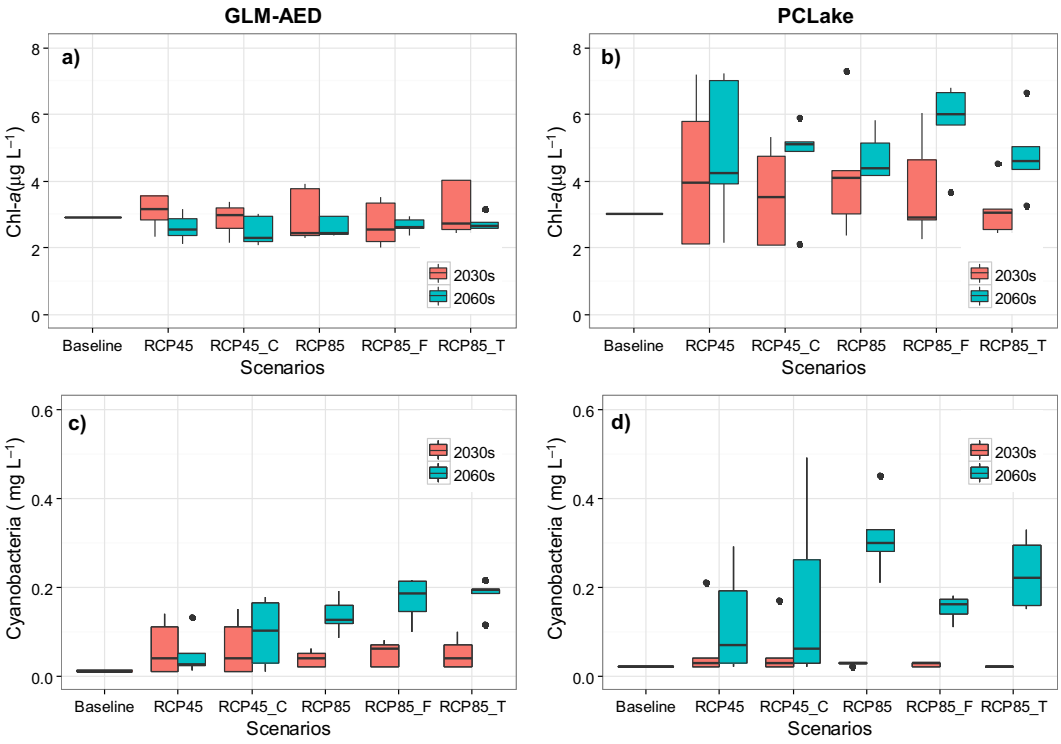

Fig. 8. Predicted a-b) Chl-*a* concentrations and c-d) cyanobacteria biomass in future scenarios. Left panel represents the results of the GLM-AED model and the right panel the results of PCLake model. RCP 4.5 and RCP 8.5: All GCMs without land use change in the RCP 4.5 and RCP 8.5 scenarios, respectively. RCP45_C: RCP 4.5 with the Consensus World Scenario; RCP 85_F: RCP 8.5 with the Fragmented World Scenario; RCP85_T: RCP 8.5 with the Techno World Scenario. Each boxplot was generated using averages of each GCM result.

can also be attributed to low concentrations as SRP and NH_4 concentrations were below detection limits (5 µg L^{-1}) most of the time. In this kind of datasets, notwithstanding the low relative error measures, R^2 values could also be low due to low variance and absence of distinct seasonality (Trolle et al., 2011b). Comparing with the comprehensive review of Arhonditsis and Brett (2004), a meta-analysis of 153 lake modeling studies, for SRP the R^2 values in both models indicated that our models performed better than the models in 20% of the studies analysed by Arhonditsis and Brett (2004). For NH_4, the outputs of PCLake indicated a performance better than 40% of the studies included in Arhonditsis and Brett (2004), while for GLM-AED, it was 20%. For NO_3, the performance of both models was poor with lower than 10% of the models. However, it should be noted that the PCLake model overestimated the inorganic nitrogen compounds, which may have affected the different responses observed at the phytoplankton level. Since Chl-*a* statistics was not included in the study of Arhonditsis and Brett (2004), we compared the statistics on Chl-*a* with recent literature (Table A.9) and found that Chl-*a* values were within the ranges presented in peer-reviewed literature. Although the calibration performance of our models was poor especially for nitrogen compounds, we increased the confidence of the results for future simulations by using two different lake models.

The GLM-AED model results showed decreased water levels in most of the scenarios for both the 2030s and 2060s in RCP 8.5 scenarios in response to increased evaporation and temperatures, and decreased precipitation. The lowest water levels occurred in the Techno World and Fragmented World land use scenarios with RCP 8.5 with increased water abstraction. However, for GFDL and IPSL GCMs with RCP 4.5 and Consensus World land use scenarios where water abstraction decreases by 10%, higher water levels were predicted (Table A.6). These results, together with those of Bucak et al. (2017), indicate that outflow management is important to sustain water levels in the Mediterranean region in a climatic change context. However, it should be noted that using the delta change approach (applying relative changes in precipitation and temperature to the baseline) and applying the future relative changes for the 2030s and 2060s to only a two-year baseline period may result in under- or overestimation of the effects of future changes. This is because the delta change approach is unable to capture the climatic variabilities and extreme events (El-Khoury et al., 2015).

GLM-AED and PCLake differed in their responses to climatic changes and land use regarding TP and TN concentrations. While the GLM-AED model results demonstrated only minor changes, nutrient concentrations increased in the PCLake runs, especially in the 2060s. These differences may be ascribed to structural differences of the lake models but may possibly also result from the calibration and the differences in nutrient fractions, especially for N compounds since the amount of inorganic nitrogen compounds being overestimated in PCLake. In addition, CIT analysis indicated that in PCLake, the system is more P limited and availability of phosphorus is one of the determinants of phytoplankton growth, which may generate different responses of the two models in terms of nutrient compounds. Furthermore, the PCLake model has a zero-dimensional structure and considered the lake surface of Lake Beyşehir constant throughout the simulation. This might have led to an

Table 6
Number of days exceeding the low-risk WHO limits for drinking water (10 mg m^{-3} cyanobacterial Chl-*a*) according to future land use and climate scenarios for the 2060s in the PCLake model. Scenario outputs not exceeding WHO limits are not included in the table.

GCMs	RCPs	Land use	Number of days exceeding WHO limits (cyanobacterial Chl-*a*)
HadGEM	8.5	Current	80
HadGEM	8.5	Techno	52
MIROC	4.5	Current	38
MIROC	8.5	Current	31
MIROC	4.5	Consensus	17
MPI	8.5	Current	29
IPSL	4.5	Current	1
IPSL	8.5	Current	46
IPSL	8.5	Techno	45
IPSL	8.5	Fragmented	64

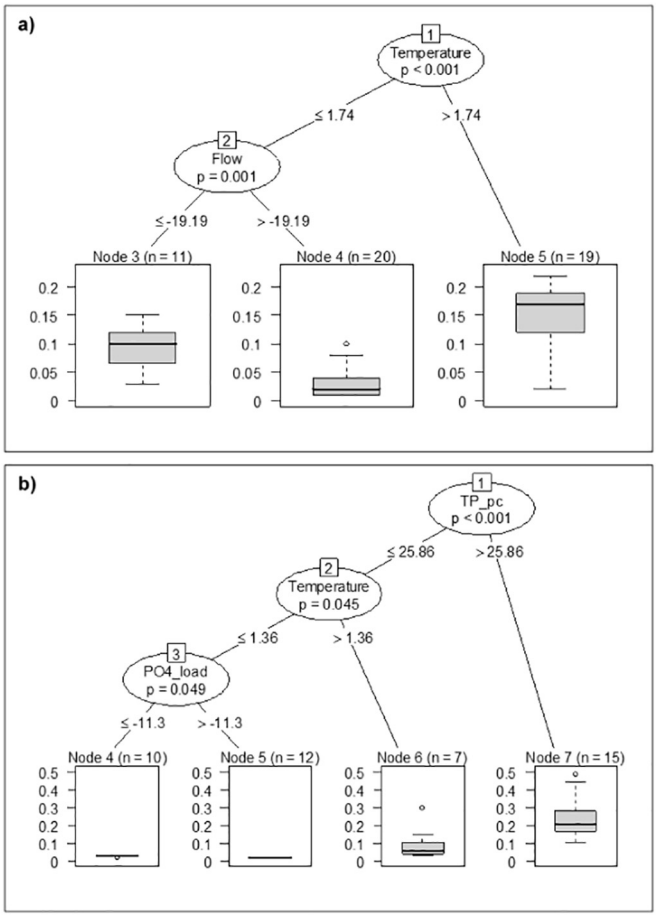

Fig. 9. Conditional inference trees display the hierarcical relationships of environmental variables on cyanobacteria biomass in a) the GLM-AED model, b) the PCLake model. Temperature: relative change to baseline, PO_4 load, and flow: % changes compared with baseline, TP_pc: lake TP concentrations simulated in PCLake model.

overestimation of evaporation, resulting in enhanced up-concentration of the nutrients, as demonstrated by Coppens (2016) who applied the PCLake model to the semi-arid Mediterranean lake, Lake Mogan. Also, sediment-water column interactions differed in model structures. PCLake considers internal loading mechanisms through temperature mediated sediment release that depends on temporally dynamic sediment nutrient pools (Janse, 2005). Hence, in addition to enhanced up-concentration through enhanced evaporation, increased temperature can trigger increased internal loading process and result in augmented nutrient concentrations. In the GLM-AED model, sediment nutrient release is related only to water column temperature and redox conditions (proxied by oxygen and nitrate concentrations), and the model does not keep track of a sediment nutrient pool, which may change through time (Hipsey et al., 2013).

It is well known that phytoplankton productivity increases with rising temperatures (e.g. Kosten et al., 2012). Climate modeling studies from temperate lakes have shown that substantial reductions of external loads are needed (up to 75% of TN and 40–50% of TP) to prevent phytoplankton blooms (Trolle et al., 2008a) in a warmer world. Examples from New Zealand lakes have also demonstrated that a 25–50% reduction of nutrient levels is needed to sustain the current trophic status of lakes in the future (Trolle et al., 2011b). Recent modeling studies of Danish lakes (temperate zone) considering a 6 °C warming scenario showed that nutrient level reductions of 75% (Nielsen et al., 2014) and 60% (Rolighed et al., 2016) are required to maintain the current concentration of Chl-*a*. Our GLM-AED results exhibited minor changes in Chl-*a* concentrations despite a significant reduction of the external nutrient load. However, especially for the 2060s, increased Chl-*a* concentrations were simulated by the PCLake model, probably owing to the increases in lake nutrient concentrations. Though the responses of the two models differed somewhat, they both highlighted the necessity of a reduction of the nutrient load to maintain the current productivity of the lakes in a future warmer climate. The GLM-AED models indicated that climate-change mediated nutrient load reductions would suffice at least for the modelled time period, however, the PCLake model results suggested that a more substantial reduction of the nutrient load may be needed. Our scenarios covered the period until the 2060s but temperatures are anticipated to rise even further at the end of the century (IPCC, 2013). Hence, we may need to consider more stringent measures (such as decreased fertilizer use, more efficient irrigation technologies, reduction of agricultural areas) to maintain low lake productivity in the future.

Both models found a considerable increase in cyanobacteria biomass for both time periods. The same has been predicted in many studies demonstrating an increase in cyanobacteria blooms with warming (Paerl et al., 2011) due to their higher optimum growth temperature (25–35 °C) (Robarts and Zohary, 1987). The CIT results of both models for cyanobacteria concurred with these findings as higher cyanobacteria growth was traced at higher temperatures. The GLM-AED outputs showed that also flow was a significant factor determining cyanobacteria biomass. Similarly, using the PROTECH model, Elliott (2010) revealed minor changes in the Chl-*a* concentration with marked changes in phytoplankton composition as a response to increasing inflow rates with higher temperatures. Flushing plays a major role in the composition of phytoplankton and enhanced flushing and mixing are known to favour green algae and diatoms over cyanobacteria due to their higher growth rate and lower sedimentation losses during mixing (Visser et al., 2015). Moreover, higher flushing is also known to limit blooms by the flushing out of nutrients (Elliott, 2010). However, it should be noted that the flushing rates of Lake Beyşehir may not be sufficiently high to have such impact since the water retention time in Lake Beyşehir lies within the range 5 years to 131 years. In addition, throughout the simulation, the TN:TP ratio was mostly below 22, below which large N-fixing cyanobacteria are favoured (Smith et al., 1995; Gophen et al., 1999). The GLM-AED model also included nitrogen fixation processes of cyanobacteria, which may also contribute to the increasing cyanobacteria biomass.

In the PCLake model, in addition to temperature, TP and SRP loads were the main factors explaining the dominance of cyanobacteria. This is consistent with the findings of Erdoğan (2016), indicating that cyanobacteria abundance was mainly driven by a synergistic nutrient-temperature interaction. High temperature and TP conditions generally favour cyanobacteria species (Paerl and Huisman, 2008, 2009) due to the high nutrient uptake ratio of cyanobacteria compared with most other algae and higher optimum growth temperatures (Janse, 2005). Concerning cyanobacteria, the two models showed differential sensitivity to changes in environmental variables. In the GLM-AED model the CIT analysis of cyanobacteria biomass showed that increased temperatures and decreased flow rates favoured cyanobacteria biomass, while in the PCLake model, the in-lake TP concentration was the major factor affecting cyanobacteria biomass, followed by temperature and SRP loading to the lake. Kane et al. (2014) also stated that not only the total amount of nutrient loading, but also the forms of nutrients important since they found clear link between SRP loading and cyanobacteria biomass, which also concurred with the results derived from PCLake outputs. Although not detected in our study, nitrogen can also be an important factor affecting phytoplankton community composition and cyanobacteria can take advantage in low nitrogen concentrations (Huisman and Hulot, 2005, Paerl and Otten, 2013). With these outcomes, we also want to highlight that, even though the models give similar outputs during the calibration period, uncertainty derived from model structure may cause variable responses for the future predictions, which emphasizes the need of using ensemble models for more robust conclusions (Trolle et al., 2014).

We also calculated the number of days where the cyanobacteria biomass exceeded the low-risk and high-risk threshold according to WHO thresholds in order to evaluate the future ecosystem service of the lake as a drinking water supply. No scenarios in the two lake models exceeded the high-risk threshold in the 2030s, but for the 2060s 10 out of 25 scenarios in the PCLake model exceeded the low-risk. These scenarios were the ones showing the most extreme reduction of flows and higher temperatures, indicating that low water levels combined with higher temperatures may pose a risk to the future water quality of Mediterranean ecosystems. Similar observations have been made in many studies showing that increased occurrences of harmful cyanobacteria blooms significantly impact ecosystem functioning (such as fish kills) and ecosystem services such as the supply of drinking and irrigation water (Havens and Schelske, 2001; Qin et al., 2010; Paerl et al., 2011).

However, low water levels may also lead to dominance by macrophytes (at least to a certain point) rather than by phytoplankton as macrophytes are able to extend their coverage at low water levels, as evidenced in many studies conducted in the Mediterranean region (Beklioğlu et al., 2006; Özkan et al., 2010; Bucak et al., 2012; Ersoy, 2015). Unfortunately, the GLM-AED model did not include macrophyte processes and despite that PCLake did included macrophyte dynamics, we did not test and validate macrophyte growth due to limited data availability. As also stated by Coppens (2016), the 0D structure of the PCLake model can be ineffective in revealing the effects of water level fluctuations on macrophyte growth. In Mediterranean lakes, water level fluctuation is a major driver of macrophyte growth (Coops et al., 2003; Beklioğlu et al., 2006) by directly affecting the area available for macrophytes and by indirectly by affecting the nutrient concentrations in the water column (Coppens et al., 2016; Beklioğlu et al., 2017). Therefore, PCLake seems to be more appropriate for temperate lakes with smaller seasonal shifts in water levels. A newly developed model by Hu et al. (2016), FABM-PCLake, may provide a new avenue for investigating the effects of water level fluctuations on macrophytes, as it enables coupling between the biogeochemical processes in PCLake and 1D or 3D hydrodynamic models.

5. Conclusion

In conclusion, the current study highlights the crucial role of nutrient control in maintaining the clear water state of Mediterranean lakes in future dry and warmer periods. Although we found differences in the magnitude of model outputs of two different lake models, their direction of responses mostly followed similar pattern, The results indicate that a significant reduction of nutrient loading will somewhat offset the effects of increased temperatures as evidenced by our finding of only minor changes in Chl-*a*. However, despite low Chl-*a* concentrations (in most scenarios), an increased abundance of cyanobacteria may, to a certain extent, deteriorate the drinking water status of Lake Beyşehir in the future. In addition, extended periods of decreased hydraulic loads from the catchment and increased evaporation may lead to water level reductions and reduced ecosystem services of the lake as an irrigation water supply. Our results also highlight the importance of land use management; for instance, in the Consensus World scenario, efficient irrigation, lower water abstraction and less fertilizer application entail a higher water yield and reduced nitrate load compared to the other scenarios. However, expansion of agricultural areas with fertilizer application will increase the nutrient leaching from the catchment despite reduced runoff. In the Mediterranean region, adoption of efficient irrigation technologies and, promotion of drought-resistant crop not only have the potential to decrease the water scarcity but also to enable a reduction of nutrient leaching from the soil. Such initiatives may mitigate the impacts of warming on lakes by preventing algal blooms and help to sustain the ecosystem services of the lake in the future.

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Appendix A. Supplementary data

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